

Review

Wearable Technologies in Occupational Safety and Health: A Systematic Review and a Human-Centered Implementation Model

David Mendes ^{1,2,*} , Elena Terradillos ^{1,2} , Helena V. G. Navas ^{3,4} , Olga Costa ^{1,2} , João Matias ^{5,6} 
and Vanessa Soares ⁷ 

- ¹ Instituto Politécnico de Setúbal, Escola Superior de Tecnologia de Setúbal, 2910-761 Setúbal, Portugal; elena.terraddillos@estsetubal.ips.pt (E.T.); olga.costa@estsetubal.ips.pt (O.C.)
 - ² DICE Lab, Escola Superior de Tecnologia de Setúbal, Instituto Politécnico de Setúbal, 2910-761 Setúbal, Portugal
 - ³ UNIDEMI, Department of Mechanical and Industrial Engineering, NOVA School of Science and Technology, Universidade NOVA de Lisboa, 2829-516 Caparica, Portugal; hvgn@fct.unl.pt
 - ⁴ LASI—Intelligent Systems Associate Laboratory, 4800-058 Guimarães, Portugal
 - ⁵ Departamento de Economia, Gestão, Engenharia Industrial e Turismo (DEGEIT), Universidade de Aveiro, Campus Universitário de Santiago, 3810-193 Aveiro, Portugal; jmatias@ua.pt
 - ⁶ GOVCOPP, Unidade de Investigação em Governança, Competitividade e Políticas Públicas, Universidade de Aveiro, Campus Universitário de Santiago, 3810-193 Aveiro, Portugal
 - ⁷ Instituto Politécnico de Setúbal, Escola Superior de Ciências Empresariais, 2914-503 Setúbal, Portugal; 230314029@estudantes.ips.pt
- * Correspondence: david.mendes@estsetubal.ips.pt

Featured Application

This study proposes a conceptual Human-Centered Integrative Model intended to support Occupational Safety and Health managers and industrial engineers in reflecting on the potential adoption of wearable technologies. By organizing insights from the existing literature into a structured four-phase framework, the work outlines key organizational and human factors relevant to the transition toward data-informed risk prevention practices. Rather than providing a validated solution, the model offers a preliminary and theory-based reference to help frame implementation processes, highlighting the need to balance sensor integration with worker trust, transparency, and ethical data governance. It is intended as a foundation for future empirical research and contextual adaptation in industrial settings.

Abstract

Wearable technologies have emerged as promising tools for supporting Occupational Safety and Health through continuous and multimodal monitoring of physiological, biomechanical, and environmental risk factors. However, evidence regarding their real-world effectiveness and implementation remains fragmented. This study presents a systematic literature review conducted in accordance with PRISMA 2020 guidelines, synthesizing evidence from 60 studies addressing wearable-based monitoring, assessment, and intervention in occupational contexts. The review examines the types of technologies applied, the risks and functions addressed, the evidence on effectiveness, the evaluation metrics used, and the main barriers affecting implementation. The findings show that wearable technologies are mainly applied to ergonomic, physiological, environmental, and critical-event risks, using devices such as inertial sensors, biosensors, smart personal protective equipment, and exoskeletons. While the evidence indicates strong potential for real-time monitoring, risk detection, and data-informed decision-making, most studies rely on controlled or short-term evaluations, and consistent evidence of sustained accident reduction remains



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limited. The results also highlight technical, organizational, ethical, and human-related barriers, including usability, interoperability, privacy concerns, worker acceptance, and data governance. Based on this synthesis, a conceptual human-centered implementation model is proposed to support responsible and context-sensitive adoption.

Keywords: wearable technologies; occupational safety and health; technology adoption; human-centered approach; risk prevention; industrial environments

1. Introduction

Occupational Safety and Health (OSH) has progressively assumed a central role in organizational strategies and in the formulation of public policies, particularly in sectors characterized by elevated levels of operational risk, such as manufacturing, construction, and extractive industries [1–4]. The increasing complexity of contemporary work environments, driven by intensified production processes, digital transformation, and the globalization of value chains, has reinforced the need for more proactive, preventive, and data-driven approaches to managing occupational risks and reducing the incidence of accidents and occupational diseases [5–8]. Within this context, the development of innovative solutions that promote safer, healthier, and more efficient working conditions has become increasingly relevant, particularly in light of the Industry 5.0 paradigm, which emphasizes the centrality of the worker and the integration of human well-being into technological advancement, requiring systems that are not only productive but also inherently safe [3,9–12].

In this evolving landscape, digitalization emerges as a key enabler of transformation, facilitating the integration of advanced technologies into production systems and safety management practices. Among these technologies, wearable devices have attracted growing attention as a promising approach within OSH [3,13–17]. For the purposes of this study, wearable technologies are defined as electronic systems designed to be worn directly on the body, embedded in clothing or personal protective equipment (PPE), enabling continuous or semi-continuous monitoring of physiological, biomechanical, and environmental parameters [5,6,17–22]. This definition encompasses a wide range of devices, including body sensors, smart bracelets, smart helmets, exoskeletons, and integrated smart PPE systems, as well as connected wearable solutions that interact directly with users to support early risk detection and real-time decision-making through feedback mechanisms [23–28].

The recent literature [5,6,11,21,29–38] highlights a significant evolution in this field, characterized by a transition from isolated sensing approaches toward integrated multimodal monitoring systems, in which multiple data sources are combined to enhance the understanding of operational conditions and strengthen preventive capabilities. Furthermore, studies [3,5,16,17,29–33] suggest that the integration of heterogeneous sensor data can contribute to reducing false alarms and improving the reliability of real-time interventions, thereby supporting more responsive safety management strategies.

Despite their recognized potential, the adoption of wearable technologies in industrial contexts remains limited and faces several challenges [3,8–10,34]. The available scientific evidence is often fragmented and predominantly based on isolated case studies, prototype developments, or context-specific applications, which makes it difficult to derive a comprehensive and integrated understanding of their effectiveness, limitations, and implementation requirements [3,8,13,35,36]. Systematic mappings [3,4,8,28,29,34,36–39] indicate that, although the technological maturity of hardware components has advanced, the integration of wearable systems into organizational processes and safety management

frameworks remains insufficient. In addition, recent studies [7,15,29,32,35,38,40–42] emphasize the lack of standardized methodologies, limited interoperability between systems, and the scarcity of large-scale validation in real industrial environments. Beyond technical constraints, factors such as user acceptance, integration with existing organizational structures, implementation and maintenance costs, operational robustness in adverse conditions, and ethical concerns related to data privacy and governance continue to influence the effectiveness and long-term viability of these solutions [4,5,10,17,34].

Given these limitations, there is a need to consolidate and critically assess the existing body of knowledge through a rigorous and systematic methodological approach. A Systematic Literature Review (SLR), conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [43–46], provides a structured and transparent framework to identify, analyze, and synthesize the available evidence, enabling the mapping of the current state of the art as well as the identification of research gaps and future directions [11,46,47].

Existing research on wearable technologies in OSH can be broadly organized around three interrelated axes: technological innovation, data intelligence, and human-centered health monitoring. In terms of technological development, studies increasingly focus on energy efficiency, system integration, and advanced sensing capabilities. Mokhtari et al. [48] highlight the potential of self-powered systems for vibration risk detection, while De Fazio et al. [18] propose integrated smart garments that combine physiological sensing with energy harvesting. Within the broader Industry 4.0 and 5.0 context, Damilos et al. [4] and Flor-Unda et al. [9] emphasize how wearable technologies, combined with artificial intelligence (AI) and virtual environments, can enable predictive and human-centered approaches to safety management.

Another important research direction relates to advanced analytics and sensor fusion. Studies by Wu and Hu [30], Xu et al. [49], Papoutsakis et al. [31], and Mahmud et al. [32] indicate that deep learning techniques and multi-source data integration have been associated with improvements in anomaly detection and the prevention of physical overload and fall-related incidents. Similarly, Antwi-Afari et al. [42] and Prisco et al. [41] suggest that machine learning approaches may enable accurate biomechanical risk assessment even with reduced sensor configurations.

From an ergonomic and occupational health perspective, wearable sensors have been increasingly explored and validated as tools for quantifying physical demands and fatigue. Studies by Sabino et al. [13], Tjøsvoll et al. [19], and Bonin et al. [25] focus on identifying harmful postures, while Coccia et al. [23], Pitzalis et al. [27], and Kim et al. [24] examine the use of exoskeletons and adaptive solutions to reduce muscular load. In parallel, the monitoring of mental well-being and environmental exposure has gained relevance, with contributions from Mohapatra et al. [40], Hijry et al. [7], and Srinivasan et al. [21] addressing stress and fatigue, alongside Callihan et al. [20] and Güntner and Schenk [22] focusing on thermal stress and air quality. Overviews provided by Chen et al. [11] and Moon and Ju [17] further reinforce the versatility of these applications across industrial and construction contexts.

Nevertheless, the literature consistently identifies significant barriers to effective and sustained implementation. Fanti et al. [36], Cannady et al. [8], and Lind et al. [28] highlight persistent challenges related to validation and standardization, while Tabatabaee et al. [34] and Doodoo et al. [3] emphasize organizational resistance and behavioral constraints. In addition, Moshawrab et al. [5] and El-Helaly [10] underline the importance of addressing data governance, privacy, and user acceptance as key components of successful implementation strategies.

In light of these challenges, this study aims to provide a comprehensive analysis of the role of wearable technologies in OSH, considering both their potential benefits and the limitations associated with their implementation in industrial contexts. The study does not assume that wearable technologies automatically lead to improved safety outcomes. Instead, it examines the types of technologies applied, their practical uses, the nature of the available evidence regarding their effectiveness, the metrics used for evaluation, and the conditions under which they can be responsibly implemented. This approach allows a clearer distinction between technological potential and empirical evidence, supporting a more critical and contextualized analysis.

To guide this investigation, the following research questions (RQs) were defined, reflecting a progressive structure from technological characterization to implementation conditions:

RQ1. What types of wearable technologies are applied in OSH, and for which occupational risks or functions?

RQ2. How are wearable technologies used to monitor, assess, and prevent occupational risks?

RQ3. What evidence exists regarding their effectiveness in improving safety-related outcomes?

RQ4. What metrics and evaluation approaches are used to assess wearable-based OSH interventions?

RQ5. What are the main barriers, limitations, and challenges affecting the real-world implementation of wearable technologies in OSH contexts?

Beyond the systematic review, this study also develops a conceptual integrative, human-centered model to support the implementation of wearable technologies in industrial environments. This model is intended to provide a structured and ethically oriented framework to assist organizations in adopting these technologies in alignment with worker needs and organizational objectives, while supporting a responsible and context-sensitive implementation approach.

The article is structured as follows. Section 2 presents the theoretical framework, addressing wearable technologies in OSH, multimodal monitoring, predictive risk analysis, and human factors, including adoption barriers such as privacy and costs. Section 3 describes the research methodology, including search strategy, inclusion and exclusion criteria, and study selection process. Section 4 presents the results of the systematic review. Section 5 discusses the findings in relation to the RQs. Section 6 proposes a conceptual model for the responsible adoption and implementation of wearable technologies. Finally, Section 7 presents conclusions, limitations, and directions for future research.

2. Background

This section presents the state of the art on wearable technologies applied to occupational health and safety, addressing the monitoring of physiological indicators, postures, and environmental conditions. It also discusses the application of AI and predictive analytics to anticipate risks and support safety decisions, as well as human factors, adoption barriers, privacy, cost, and technological acceptance in the workplace context.

2.1. Multimodal Sensing in OSH

The digital transformation associated with Industry 4.0 has significantly driven the adoption of wearable technologies as advanced tools for managing occupational health and safety. These devices enable continuous and real-time monitoring of multiple risk factors, helping to overcome some limitations of traditional approaches based on point measurements, retrospective assessments, and reactive safety management [4,6,17,29,36,42,50,51]. Recent studies [3,10,16,31,34,37,49] show that the integration of smart sensors can con-

tribute to the early identification of hazards, particularly in complex and high-risk industrial environments.

In the physiological domain, wearable devices enable the monitoring of biometric indicators such as heart rate, heart rate variability, skin conductance, and body temperature, which may support the detection of fatigue, stress, and physical overload [5–8,33]. Recent literature [5,7,10,37,41,42,49,52] highlights the application of machine learning models to the analysis of these signals, allowing the identification and prediction of risk-related conditions in specific experimental or operational contexts. These approaches have been particularly explored in sectors such as construction and manufacturing, where fatigue and occupational stress are associated with increased accident susceptibility and reduced safety performance [11,33,39,40,50].

Biomechanical monitoring has evolved through the use of inertial measurement units, which enable continuous assessment of posture, body movements, and exposure to repetitive strain. These systems provide objective data on workers' physical behavior, complementing traditional observation-based methodologies. Their application supports the identification of risk factors associated with musculoskeletal disorders, as well as the implementation of real-time feedback mechanisms for postural correction, being particularly relevant in industrial and logistics contexts [13,16,23,25,26,28,29,33].

In parallel, environmental sensors integrated into wearable devices allow the detection of chemical and physical hazards, including toxic gases, suspended particles, noise, and thermal stress. Recent technologies incorporate electrochemical sensors and environmental modules directly into PPE, enabling continuous exposure monitoring and timely responses to hazardous conditions. These data provide relevant contextual information for understanding the interaction between the work environment and workers' physiological responses [4,8,17,18,21,36,48,53].

One of the most relevant advances in this field lies in the transition from approaches based on isolated sensors to integrated multimodal systems. Instead of analyzing each dimension independently, current solutions increasingly use the fusion of physiological, biomechanical, and environmental data, allowing a more comprehensive view of the worker's condition and the surrounding work context. This integration enables the identification of complex relationships between risk factors and can improve prevention capabilities and decision support when supported by reliable data processing and appropriate organizational integration [5,10,21,30,31,33].

Despite these advances, significant limitations persist in the literature. There is substantial heterogeneity in sensor configurations, data collection methodologies, and analysis procedures, making comparisons between studies difficult [7,25,28,36,42,54]. Furthermore, empirical evidence on the direct impact of wearable technologies on accident reduction in real-world contexts remains limited [3,7–9,17,32–34,42]. Challenges related to interoperability, standardization, ecological validity, and large-scale validation continue to restrict their widespread adoption and the generalizability of the findings.

2.2. AI and Predictive Analytics for Proactive Risk Prevention

The increasing use of wearable technologies in industrial environments has led to the generation of large volumes of data, whose usefulness depends on the ability to transform them into relevant and actionable information for risk prevention. Data collection alone is not sufficient to improve worker safety; advanced analytical techniques are required to extract meaningful knowledge in a timely and context-sensitive manner [10,17,21,28,36,48].

In this context, AI and machine learning play an essential role in creating predictive models capable of identifying complex patterns in multimodal data streams [4,10,48,49]. These models can support the anticipation of risk situations through the early detection of

physiological, behavioral, or environmental anomalies. Recurring examples include fatigue prediction based on heart rate variability and plantar pressure, as well as the identification of inadequate postures or hazardous environmental conditions [3,5,10,17,18,26,32,33,42].

The application of these technologies in operational contexts may enable the development of proactive monitoring systems supported by real-time alerts and decision-support interfaces. These systems can contribute to the dynamic adaptation of working conditions, promote preventive interventions, and reduce exposure to occupational risks. Additionally, they may support data integration at the organizational level, facilitating safety management and the development of evidence-based strategies [3,6,8,10,17,30,55].

However, the transition from data acquisition to safe action is not automatic. The effectiveness of predictive systems depends not only on the accuracy of algorithms, but also on how information is perceived, understood, and translated into decisions by workers, supervisors, and organizations. In this sense, situational awareness represents an important cognitive mechanism linking the perception of risk cues, the comprehension of their meaning, the anticipation of possible consequences, and the selection of appropriate responses [56]. This perspective reinforces the need to design wearable-based decision-support systems that provide interpretable, timely, and context-relevant feedback rather than merely increasing the volume of available data.

Nevertheless, the literature [5,6,8,11,17,27,28] reveals significant limitations that restrict the practical application of these approaches. Many studies are based on small datasets obtained in controlled environments, which compromises the generalizability of the results to dynamic and heterogeneous workplaces. There is also weak integration with existing organizational and regulatory processes, as well as a high dependence on specific technological infrastructures.

Although predictive analytics technologies show high potential for supporting occupational risk prevention [10,22,30,32,41,42], their implementation in real-world contexts remains limited [3,13,36,48]. This gap highlights the need for integrated approaches that combine analytical capabilities with organizational and human factors, promoting a more effective and responsible application of these solutions [3,4,10,25,34]. The effectiveness of these approaches therefore depends not only on technical performance, but also on their acceptance, interpretability, integration into work routines, and alignment with human and organizational contexts [4,10,13,20,23,24,34].

2.3. Human Factors and Implementation Barriers

The implementation of emerging technologies in the workplace does not, in itself, guarantee the success of safety interventions, as the effectiveness of these tools depends on their appropriate integration with workers, work processes, and organizational systems [3,4,10,13,20,21,23]. The human factor plays a central role in this process, since technology should be understood as a complement to human capabilities rather than as an isolated solution [3,4,10,19,25,31]. The literature [3,4,10,21,42,48] indicates that neglecting the needs, expectations, and characteristics of end users can compromise the adoption and effectiveness of technically advanced systems. Thus, the transition toward intelligent safety requires a deep understanding of the interactions between workers, devices, tasks, and organizational conditions [13,19,20,23–25,30].

User trust and perceptions of wearable devices are key factors influencing acceptance in the workplace. Significant concerns exist regarding continuous monitoring and the potential use of technology to evaluate downtime or productivity rather than solely promoting safety [3,4,10,20,23,25,31]. This perception of excessive control can generate anxiety and resistance among employees, hindering adoption [3,4,13,21,42]. Studies [3,10,20,23–25,32,48] indicate that a considerable proportion of workers express reservations about constant

monitoring, making the establishment of a relationship of trust between management and the workforce an important condition for implementation.

Privacy and ethical issues represent significant obstacles that organizations must address when implementing monitoring sensors. The collection of sensitive data and personal biometric information requires strict compliance with regulations such as the General Data Protection Regulation [4,5,9,25,27,30,48]. It is necessary to ensure that employee consent is obtained clearly and that robust data governance policies are in place to prevent leaks, unauthorized access, or misuse [3,4,10,20,21]. Transparency regarding who has access to the data, how long data are stored, and for what purposes they are used is an essential ethical requirement to protect user dignity and maintain trust in the workplace [3,4,10,25,31,32]. Recent privacy-focused studies on wearable technologies further emphasize the importance of data minimization, transparency, access control, and clear governance mechanisms to reduce surveillance concerns and strengthen user trust [57,58].

Organizational barriers, including high acquisition and maintenance costs, continue to hinder the widespread dissemination of wearable technologies. Beyond financial investment, there is a need for adequate technical training for both workers and supervisors, so that systems can be operated safely and the generated data can be interpreted correctly [3,4,7,8,10,13,25,28,41]. A lack of a safety culture that supports digital innovation can result in low confidence in new solutions and the persistence of less efficient traditional methods [3,5,6,27]. Therefore, the integration of intelligent systems requires structural adaptation and active support from senior management to align technology with occupational health and safety objectives [3,4,10,11,30,35,36,40,59].

In addition to technical and organizational barriers, psychosocial factors also influence the effectiveness of wearable technologies. Safety behavior is shaped not only by information availability, but also by emotional states, perceived self-efficacy, team dynamics, fatigue, and the broader psychosocial climate of the workplace. Workers experiencing emotional exhaustion or low safety self-efficacy may respond differently to monitoring systems, alerts, or feedback mechanisms, which suggests that wearable technologies should be implemented within broader strategies that consider psychological and social determinants of safety behavior [60]. This perspective helps move beyond a purely technical framing and reinforces the need to integrate organizational psychology and human factors into wearable-based safety interventions.

Analysis of current literature [7,22,26,31,32,40,42,49] reveals that technical studies dominate the research field, with a clear predominance of approaches focused on sensor precision and algorithm development. There is a scarcity of research that deeply integrates a human-centered perspective or assesses the long-term psychological impact of these tools [3,5,6,11,21,34]. The lack of structured frameworks to guide practical implementation while simultaneously considering technical, human, and organizational factors constitutes a significant gap in the available scientific evidence [8,9,17,25,28,36,61]. This disconnect between technological development and practical implementation may hinder the development of effective and sustainable interventions in real-world industrial environments. The contrast between technical potential and acceptance barriers highlights the need for implementation structures that are not focused solely on hardware, but on integrative socio-technical approaches [3,5,8,25,27,28,34,35].

Taken together, these limitations highlight the need for structured and integrative approaches that go beyond isolated technological solutions, supporting the development of frameworks capable of addressing the interaction between technological capabilities, human factors, and organizational conditions.

3. Materials and Methods

This section describes the research methodology adopted, including the procedures used for collecting, selecting, and analyzing the scientific literature. The methodological approach, data sources and search strategy, inclusion and exclusion criteria, as well as the data selection and extraction process are presented in a structured manner.

3.1. Methodological Approach

Literature reviews play a central role in scientific research, as they enable the identification of the state of the art, the mapping of knowledge gaps, and the foundation for new research directions. Among the different types of reviews, SLRs stand out due to their high methodological rigor, based on structured procedures and explicit criteria. In contrast, other approaches, such as narrative or integrative reviews, offer greater flexibility but less standardization, which may increase susceptibility to bias [46,62–64].

This study adopted a SLR as its methodological approach, aiming to identify, analyze, and synthesize empirical evidence on the impact of wearable technologies on OSH. This approach was considered the most appropriate, as it enables a comprehensive, structured, and transparent analysis while ensuring the consistency and credibility of the results. SLRs are characterized by being systematic, explicit, and comprehensive, allowing the identification, evaluation, and synthesis of existing knowledge, while minimizing bias and maximizing process traceability [46,65,66].

To ensure scientific rigor and transparency, the PRISMA protocol was followed. This widely recognized framework guides all stages of the review process, from study identification to selection and inclusion, ensuring the replicability and reliability of the findings [6,43,65,67].

This approach is particularly suitable for this study given the rapid evolution and multidisciplinary nature of wearable technologies applied to OSH.

3.2. Data Sources and Search Strategy

The bibliographic search was conducted in Web of Science (WoS) and Scopus databases, selected due to their high scientific relevance, broad thematic coverage, and international recognition in the fields of engineering, industrial management, occupational health, and emerging technologies [45,51]. These databases index peer-reviewed scientific literature and are widely used in systematic reviews, being considered reliable sources for studies of this nature.

The search strategy was designed to identify studies addressing the application of wearable monitoring technologies in OSH contexts. To achieve this, search terms were combined using Boolean operators [47,68] and applied to the title, abstract, and keyword fields, ensuring both accuracy and replicability.

The final search string used was: ("wearable technolog*" OR wearable* OR "body-worn sensor*" OR "wearable sensor*" OR "smart sensor*" OR "inertial measurement unit*" OR IMU OR biosensor* OR "smart PPE" OR exoskeleton* OR "smart helmet*" OR "smart vest*") AND ("occupational safety" OR "occupational health" OR "workplace safety") AND (ergonomic* OR "risk assessment" OR monitoring OR evaluation OR detection) AND (worker* OR employee* OR workplace OR industry).

Bibliographic references were managed using Mendeley, which enabled duplicate detection, organization based on eligibility criteria, and efficient support for the subsequent systematic analysis.

Despite the comprehensive search strategy, some relevant studies may not have been captured due to database selection and indexing variability or variations in terminol-

ogy. However, this methodological choice ensured thematic focus and consistency in the retrieved literature.

The search strategy and selection criteria were designed to ensure alignment with the RQs, particularly regarding technological applications, implementation contexts, and evaluation outcomes.

3.3. Inclusion and Exclusion Criteria

Within the adopted methodological framework, inclusion and exclusion criteria were defined to ensure the relevance, quality, and thematic consistency of the selected studies.

Eligible studies were scientific publications written in English that addressed the application of wearable technologies in the context of OSH, providing empirical results, methodological developments, or structured analytical approaches relevant to the assessment, monitoring, or evaluation of occupational risks.

Only studies involving the direct application or evaluation of wearable technologies in OSH contexts were considered eligible.

Study selection was operationalized through the application of automatic filters in the databases, restricting results to the document types “article”, “conference paper”, and “review”.

Duplicate records, inaccessible documents, and studies that did not fit the scope of the research were excluded. In particular, studies were removed if they did not involve wearable-based monitoring, were not related to OSH contexts, or did not provide relevant analytical or empirical contributions.

It should be noted that the adopted criteria introduce certain limitations. Restricting the search to English-language publications may have led to the exclusion of relevant studies published in other languages. Additionally, the methodological heterogeneity of the included studies, encompassing different research designs, limits direct comparability and may affect the robustness of the overall synthesis.

Furthermore, due to the methodological heterogeneity of the included studies, a quantitative meta-analysis was not feasible.

3.4. Data Selection and Extraction Process

The study selection process was conducted in accordance with the PRISMA 2020 guidelines, as illustrated in the flow diagram presented in Figure 1 (see Supplementary Materials).

The initial search yielded a total of 742 records, comprising 271 from WoS and 471 from Scopus. After applying automatic filters related to document type and language, 45 records were excluded, resulting in 697 articles for further analysis.

Subsequently, 228 duplicate records were identified and removed, reducing the dataset to 469 unique studies. These were subjected to a screening phase based on title and abstract review, during which 379 articles were excluded for not meeting the predefined eligibility criteria, particularly due to lack of relevance to wearable technologies or absence of an OSH context.

As a result, 90 studies were considered potentially relevant and selected for full-text assessment. However, 11 of these were not accessible, leading to a total of 79 articles evaluated for eligibility.

Following full-text analysis, 19 additional studies were excluded, primarily due to the absence of direct wearable applications, lack of relevance to OSH contexts, or insufficient empirical validation.

Consequently, the final sample consisted of 60 articles, which were included in the detailed analysis and bibliometric study.

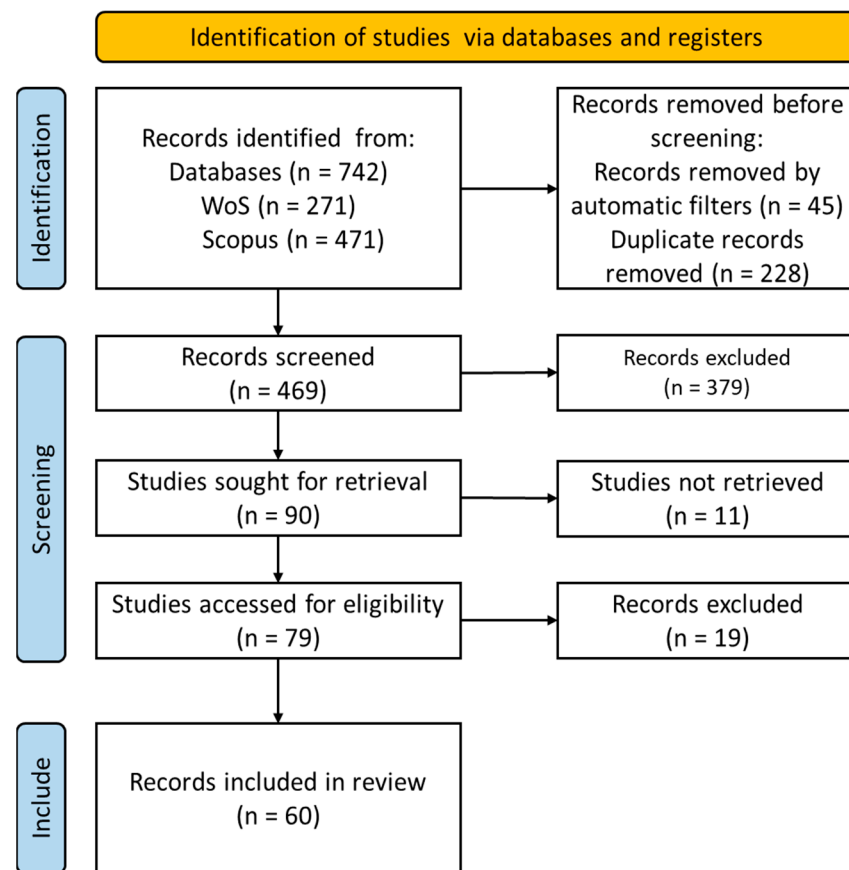


Figure 1. PRISMA flowchart for selecting studies on wearables in OSH.

3.5. Evaluation of the Methodological Quality of the Included Studies

To ensure the scientific robustness and reliability of the findings, the methodological quality of the 60 included studies was systematically assessed using a structured evaluation matrix adapted from the Joanna Briggs Institute (JBI) [69,70] critical appraisal tools. This approach ensured transparency and analytical rigor while accommodating the methodological diversity of the selected studies, including experimental studies, field studies, system development research, feasibility studies, and prototype-based investigations.

Each study was assessed according to seven criteria: (i) clarity of the research objectives, (ii) definition of the application context, (iii) appropriateness of the methodology, (iv) rigor of data collection or empirical basis, (v) coherence of the analysis, (vi) relevance of the results to OSH, and (vii) discussion of study limitations. Each criterion was rated using a three-level scale: “Yes”, “Partially”, or “No”, corresponding to scores of 1, 0.5, and 0 points, respectively. This scoring procedure allowed the calculation of an overall methodological quality score ranging from 0 to 7.

Based on the overall score, studies were classified into three methodological quality categories: high quality (≥ 6.5), moderate quality (5.5–6.0), and low quality (≤ 5.0). The assessment was independently conducted by two reviewers. To evaluate consistency between reviewers, an inter-rater agreement matrix (confusion matrix) was calculated, and Cohen’s kappa coefficient was used (Table A2). The two reviewers agreed on 55 out of 60 classifications, corresponding to an agreement rate of 91.7%. Cohen’s kappa was 0.83, indicating an almost perfect level of inter-rater agreement. Disagreements occurred only between the high and moderate categories and were resolved through discussion until consensus was reached.

The final quality appraisal indicated that a substantial proportion of studies presented high methodological quality, reflecting clear objectives, well-defined contexts, appropriate

methods, coherent analyses, and relevant results. A smaller proportion of studies was classified as moderate quality, mainly due to partial limitations in data collection procedures, empirical validation, or the discussion of limitations. Only a limited number of studies were classified as low quality, generally corresponding to conceptual, preliminary, or prototype-based studies with weaker empirical grounding.

The methodological quality assessment was not used as an exclusion criterion. Instead, it was used to support a more critical and contextualized interpretation of the evidence, giving greater analytical weight to studies with stronger methodological rigor while acknowledging the limitations of less robust studies. The complete methodological evaluation, including individual scores and final classifications, is presented in Appendix A (Table A1). The inter-rater agreement matrix used to support the reliability assessment is presented in Appendix A (Table A2).

Finally, it should be noted that the included studies show considerable methodological heterogeneity. While this diversity enriches the scope of the review by capturing different technological applications and evaluation contexts, it also limits the direct comparability of findings and should be considered when interpreting the overall conclusions of this review.

4. Results

This section presents the results of the SLR, beginning with an analysis of the included studies and continuing with the temporal distribution of the publications. This is followed by a presentation of the geographical distribution of the publications, their classification by study type, journal, and publisher, and finally, an analysis of the keywords.

4.1. Analysis of Included Studies

To organize and systematize the evidence, a qualitative analysis of the 60 included studies was conducted, considering their research objectives and main contributions. The extracted data were structured in an analysis matrix (Appendix A, Table A3), including the categories: reference, research objective, and main contributions.

The qualitative synthesis reveals a clear predominance of experimental and technology-driven studies, with a strong focus on the development, validation, and application of wearable systems for OSH. Most studies investigate wearable sensors and smart PPE designed to monitor physiological parameters (e.g., heart rate, stress indicators, temperature), biomechanical variables (e.g., posture, movement, fatigue), and environmental conditions (e.g., heat stress, toxic gases, particulate exposure).

A major thematic cluster identified across the studies relates to real-time monitoring and predictive analytics. Several works propose machine learning-based approaches to detect fatigue, stress, ergonomic risk, or hazardous events such as falls and near-falls. These approaches demonstrate high predictive accuracy and highlight the transition from reactive safety management toward proactive and preventive strategies enabled by wearable technologies.

Another relevant group of studies focuses on exoskeletons and assistive wearable devices. While some findings indicate benefits in reducing muscle activity and perceived physical strain, other studies highlight limited improvements in posture and potential negative effects on balance or usability. This reflects ongoing challenges in the practical implementation and acceptance of such technologies in real work environments.

Additionally, a significant number of studies address smart PPE and IoT-based systems, integrating multiple sensors, wireless communication, and cloud or edge computing. These solutions enable continuous monitoring, real-time alerts, and improved emergency response, particularly in high-risk environments such as construction, mining, and industrial operations.

Despite the strong technological emphasis, several studies also highlight human and organizational factors, including usability, comfort, worker acceptance, and safety culture. These aspects are critical for successful adoption and long-term implementation, reinforcing the multidimensional nature of wearable technology integration in OSH.

Regarding methodological tendencies, the results confirm the dominance of quantitative and experimental approaches, often supported by laboratory validation and, in some cases, field testing. However, prototype-based and feasibility studies remain common, frequently presenting limitations related to sample size, real-world validation, or long-term deployment.

In addition to the qualitative synthesis, a bibliometric overview was conducted to identify general trends in the literature. The results indicate a progressive increase in publications from 2020 onwards, with a marked acceleration from 2023, reflecting growing scientific and industrial interest in wearable technologies for OSH. The studies are geographically distributed across technologically advanced regions and span multiple disciplines, including engineering, occupational health, ergonomics, and computer science, confirming the interdisciplinary nature of the field.

Overall, the analysis demonstrates that wearable technologies are emerging as relevant tools for supporting OSH management, particularly through real-time monitoring, data-driven decision-making, and personalized risk assessment. However, challenges related to usability, validation in real-world conditions, and integration into organizational practices remain critical areas for future research.

4.2. Temporal Distribution of Publications

The temporal distribution of publications provides insights into the evolution of scientific interest in wearable technologies applied to OSH over time. The results reveal a clear upward trend in recent years, with a marked increase in the volume of publications (Figure 2). The including the most recent years (2025–2026), with 13 publications each, indicating a significant expansion of research activity in this field.

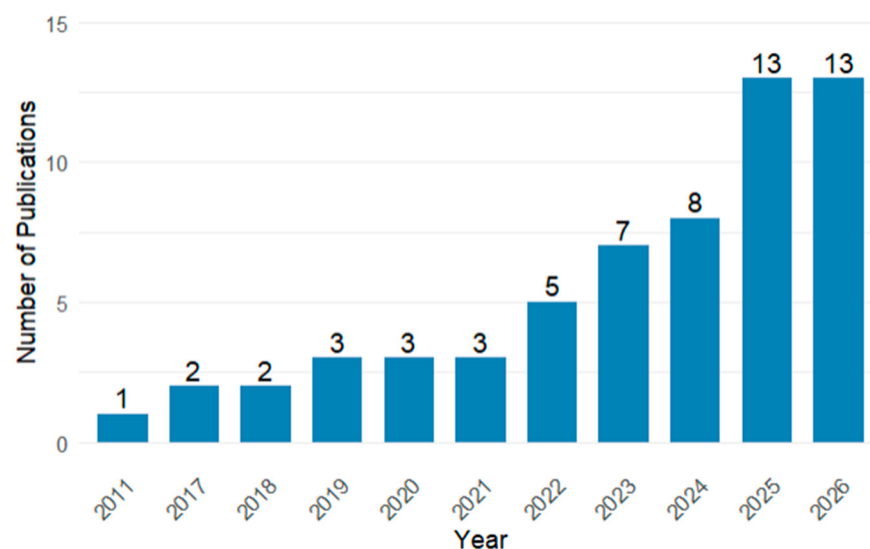


Figure 2. Evolution of the number of publications on wearables applied to OSH.

In the preceding years, a progressive growth pattern is also observed, with 8 publications in 2024 and 7 in 2023, suggesting a consolidation of the topic within the academic literature. Between 2020 and 2022, the number of publications remained moderate, ranging from 3 to 5 studies per year. In contrast, the period prior to 2020 is characterized by lower and more irregular scientific output.

Overall, these findings indicate that research on wearable technologies in OSH has gained increasing momentum, particularly since 2023. This growth can be associated with technological advancements in sensor systems, the Internet of Things (IoT), and AI, as well as a growing emphasis on real-time monitoring and proactive risk prevention in workplace environments.

4.3. Geographic Distribution of Publications

Research on wearable technologies applied to OSH demonstrates a strong international dimension, involving contributions from 28 different countries, based on the institutional affiliations of the authors (Figure 3).

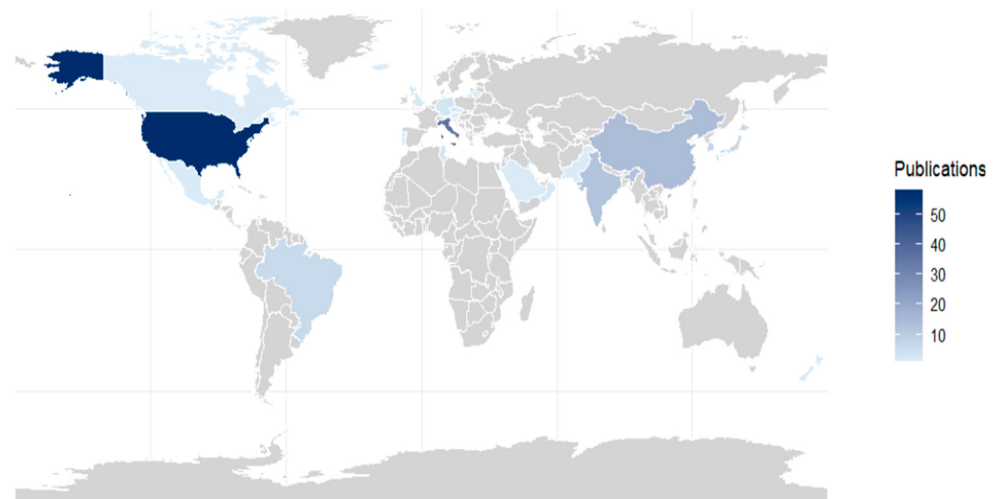


Figure 3. Global distribution of research on wearables in the OSH, highlighting the countries with the highest scientific output.

The analysis reveals a clear concentration of research activity in a small group of countries. The United States assumes a leading position, accounting for 58 contributions (32.4%), followed by Italy with 36 (20.1%). China and India also present significant participation, with 14 (7.8%) and 12 (6.7%) contributions, respectively, reflecting the growing interest and investment in wearable technologies within these regions.

A second group of countries shows moderate but consistent involvement, including South Korea with 7 contributions (3.9%), and Brazil, Denmark, and Japan, each with 6 contributions (3.4%). In contrast, countries such as France, Germany, Israel, and Tunisia exhibit more limited participation, with 3 contributions each (1.7%).

Additionally, a broader set of countries, including the Czech Republic, Hong Kong, Kuwait, Norway, Oman, and the United Kingdom, present smaller but still relevant contributions, while several others, such as Portugal, Canada, Mexico, and New Zealand, appear with isolated contributions (0.6%), reflecting a wide geographical dispersion of research efforts.

Overall, this distribution highlights a pattern characterized by strong leadership from a few countries alongside a broad international spread. This suggests that, although the field remains concentrated in specific regions, wearable technologies in OSH are gaining global relevance and are being explored across diverse industrial and cultural contexts.

Figure 3, presented as a heat map, illustrates this geographical distribution, highlighting both the main centers of scientific production and the international dissemination of the topic.

4.4. Distribution of Publications by Type, Journal and Publisher

The analysis of the 60 publications included reveals that the majority correspond to journal articles, totaling 43 publications (71.7%), while 17 works (28.3%) are from conference proceedings, reflecting the dissemination of research through academic and technological channels.

Regarding journals and conferences, a wide diversity of sources was observed, highlighting the interdisciplinary nature of the field. The most representative journals include *Sensors* and *Safety Science*, with 6 publications each, followed by *Applied Ergonomics* with 3, and *IEEE Access*, *Ergonomics*, *International Journal of Industrial Ergonomics*, and *Electronics*, with 2 publications each. Among conference events, several initiatives organized by the IEEE and other international conferences specializing in wearable technologies, IoT, and intelligent systems stand out.

Regarding publishers, there is a significant concentration in a few publishers. IEEE leads with 21 publications (35%), followed by Elsevier with 19 (31.7%) and MDPI with 10 (16.7%). Other publishers, including Springer, Taylor & Francis, ACS, among others, represent 13.3% of the sample. This distribution highlights the predominance of publishers specializing in engineering, information science, and technology applied to occupational health and safety.

Overall, the distribution by publication type, journal, and publisher reflects the interdisciplinary and evolving nature of research on wearable technologies in OSH, combining contributions from engineering, ergonomics, health science, and information technology, and highlighting the growing relevance of the topic in both academic settings and international technical events.

4.5. Keyword Analysis

The systematic review identified 351 distinct keywords in the 60 articles analyzed, highlighting the thematic diversity and multidisciplinary nature of research on wearable technologies applied to OSH. This keyword study was conducted to identify the main themes and research areas associated with wearable technologies in the context of OSH. A total of 351 distinct keyword occurrences were identified, reflecting the thematic diversity of the included studies.

Figure 4 presents the word cloud, in which the size of the terms is proportional to their frequency of occurrence, allowing a visualization of the most recurrent concepts.

The results show that the most frequent terms are directly related to the technological and applicational core of the domain under study. “Wearable sensors” (3.1%), “machine learning” (2.3%), “occupational health” (1.7%), and “workplace safety” (1.7%) stand out.

Additionally, terms such as “wearable devices,” “wearable technology,” and “wearable sensor” reinforce the dominant presence of wearable technologies, while concepts like “ergonomics,” “occupational safety,” and “industrial safety” are associated with the application context.

The presence of keywords associated with data analysis techniques and computational intelligence is also observed, namely “machine learning”, “artificial intelligence”, “deep learning” and “data analysis”.

In the field of applications, terms related to physiological and ergonomic monitoring stand out, such as “health monitoring,” “physiological monitoring,” “heart rate,” “fatigue,” “fatigue monitoring,” and “musculoskeletal disorders”.

At the same time, terms associated with event detection and risk assessment are identified, such as “fall detection,” “risk assessment,” “exposure assessment,” and “hazard detection”.

heat strain, indicating a shift from traditional safety monitoring toward a broader approach that also includes occupational health and well-being [7,73,74,81,91–96].

Smart PPE represents another important category, integrating environmental sensors and communication systems into helmets, garments, gloves, footwear, and other protective devices. These systems support the detection of external hazards, such as toxic gases, radiation, noise, vibration, and temperature extremes, while also enabling compliance monitoring and real-time alerts through IoT infrastructures [42,75,78–80,94,97,98].

Assistive wearable devices, particularly exoskeletons, differ from the other categories because they are not limited to monitoring. Instead, they act directly on risk mitigation by reducing biomechanical load during physically demanding tasks, such as manual material handling or overhead work. Their main purpose is to reduce fatigue and prevent musculoskeletal disorders [71,77,83,90,99–102].

Across the reviewed literature, wearable technologies are mainly applied to ergonomic, physiological, environmental, and critical-event risks. Functionally, they support monitoring, assessment, early warning, compliance verification, and, in some cases, direct physical assistance. Therefore, wearable technologies should not be understood as a single solution, but as an integrated technological ecosystem combining sensing, analysis, communication, and intervention capabilities, supporting the transition toward more proactive and data-informed approaches to occupational risk management [29,84,88,91,103–105].

These findings directly address the RQ by demonstrating how different types of wearable technologies are associated with specific occupational risks and functional roles in safety and health management [7,95,103,106].

5.2. RQ2—How Are Wearable Technologies Used to Monitor, Assess, and Prevent Occupational Risks?

The analysis of the included studies demonstrates that wearable technologies are used in an integrated way to transform occupational health and safety management, structured around three main functions: continuous monitoring, data-driven risk assessment, and proactive prevention [7,77,94,101,105,106].

Monitoring constitutes the first functional level, allowing for the continuous and real-time collection of physiological, biomechanical, and environmental data without interfering with task execution. Through sensors incorporated into wearable devices, it is possible to track parameters such as movement patterns, work postures, muscle activity, heart rate, body temperature, and exposure to environmental agents such as toxic gases, noise, or extreme temperatures [75,103,104,107–110]. This capability helps to make visible risks that were previously difficult to measure objectively and continuously, reinforcing the potential of these technologies, although empirical evidence regarding their direct impact is still limited [59,71,74,80,81,102].

Risk assessment involves transforming collected data into interpretable and actionable information. In this context, the literature highlights the increasing use of data analysis and AI-based approaches, which allow for the classification of risk states, identification of exposure patterns, and anticipation of critical situations [7,74,76,111,112]. The use of machine learning models and biomechanical analysis methods enables a more objective and personalized assessment, reducing dependence on traditional methods based on manual observation or self-assessment. Additionally, the integration of contextual factors, such as task or worker characteristics, contributes to improving the accuracy of the analysis and reducing the occurrence of false alarms [87,88,96,105,113].

Prevention represents the third level of action, focusing on mitigating risks and anticipating adverse events. Wearable systems allow for real-time alerts when hazardous conditions are detected, through visual, auditory, or tactile signals directed at the worker and, in some cases, supervisors [75,77,81,84,97,98]. In addition to early detection, some

technologies offer direct intervention mechanisms, such as exoskeletons, which reduce the physical load associated with demanding tasks. In parallel, the collected data can be used to support organizational decisions, including break planning, task reorganization, and the development of prevention-oriented training strategies [90,99,100,114–116].

Overall, the results indicate that wearable technologies are used not only as monitoring tools but also as integrated decision support systems capable of linking data collection to preventive action [74,80,98,111]. However, the available empirical evidence focuses predominantly on their ability to detect and monitor risks, and is still limited and often indirect with regard to their impact on reducing accidents or sustainably improving safety outcomes. Thus, the use of these technologies primarily reflects an evolution towards more predictive, personalized, and data-driven risk management models [76,86,106,110,113].

5.3. RQ3—What Evidence Exists Regarding Their Effectiveness in Improving Safety-Related Outcomes?

The analysis of the included studies indicates that the evidence regarding the effectiveness of wearable technologies in improving OSH outcomes is growing, yet remains heterogeneous and, in many cases, indirect [77,83,94,103,115]. Overall, this evidence can be structured into four main dimensions: technical performance in risk detection, impact on physical and physiological load, influence on safety-related behavior, and limitations observed in real-world contexts [83,88,90,107].

Regarding technical performance, the literature reports high levels of accuracy in the detection and classification of risk-related states [71,79,82,103,106]. Systems based on inertial sensors, physiological biosensors, and machine learning algorithms demonstrate strong capabilities in identifying non-neutral postures, fatigue levels, thermal stress, and critical events such as falls or near-falls. These findings highlight the potential of wearable technologies to support early risk detection and enhance real-time responsiveness [7,74,80,84,94,97,110].

In terms of physical and physiological impact, several studies, particularly those focusing on exoskeletons and smart garments, report significant reductions in muscle activation, perceived fatigue, and thermal load [77,83,90,100,117]. These effects suggest relevant benefits in preventing musculoskeletal disorders and managing physical strain in demanding tasks [82,92,100,101]. However, the results are not consistent across studies, with variability depending on the type of technology, application context, and real working conditions [28,99–101,109].

From a behavioral perspective, wearable technologies appear to contribute to improved risk perception, enhanced situational awareness, and safer work practices. The use of real-time feedback systems and integration with training environments has been associated with improvements in safety-related task performance [71,73,111,116]. Nevertheless, most of this evidence is derived from experimental settings or controlled environments, with limited validation in long-term operational contexts [74,76,86,110,112].

At the same time, the literature identifies several limitations that affect the effectiveness of these technologies [7,74,76]. These include discrepancies between laboratory and field performance, potential adverse effects such as movement restrictions in assistive devices like exoskeletons, and issues related to comfort, usability, and user acceptance. Such factors may significantly influence both adoption and real-world impact [7,72,74,79,92,100].

Overall, the findings suggest that wearable technologies hold strong potential for enhancing risk detection, supporting decision-making, and contributing to incident prevention. However, the current evidence base remains insufficient to consistently demonstrate a direct and sustained impact on accident reduction or long-term safety outcomes. Therefore, their effectiveness should be interpreted with caution, requiring further validation through longitudinal and real-world studies [78,80,84,86,94,98,106].

5.4. RQ4—What Metrics and Evaluation Approaches Are Used to Assess Wearable-Based OSH Interventions?

The analysis of the included studies indicates that the evaluation of wearable-based OSH interventions relies on a multidimensional set of metrics and approaches, combining technical performance indicators, physiological and biomechanical measurements, and subjective user-centered assessments [83,89,94,96,104,107,118].

From a technical perspective, the performance of wearable systems, particularly those incorporating machine learning algorithms, is commonly evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score [7,71,79,87,91,106]. These metrics are primarily used to assess the capability of the systems to correctly detect and classify risk-related states, including fatigue, hazardous postures, or critical events such as falls. In addition, validation techniques such as cross-validation and confusion matrix analysis are frequently employed to assess model robustness and generalizability across different users and contexts [41,76,82,88,119,120].

In addition to technical evaluation, physiological and biomechanical metrics are widely used to assess the impact of wearable technologies on workers' physical condition and exposure to risk. Common indicators include heart rate, heart rate variability, skin or core temperature, and electrodermal activity, which provide insight into physical workload, stress, and thermal strain [74,76,80,81,97,113]. Biomechanical evaluation is often based on measurements of joint angles, body posture, and muscle activity, typically assessed through inertial sensors and surface electromyography. These metrics enable objective quantification of ergonomic risk and physical strain, supporting the assessment of intervention effectiveness in reducing musculoskeletal load and associated occupational risk exposure [71,82,99–101].

Beyond objective measurements, subjective evaluation approaches play a critical role in assessing usability, comfort, and user acceptance. Tools such as perceived exertion scales, workload assessment indices, and usability questionnaires are frequently used to capture workers' perceptions of effort, discomfort, and cognitive load [7,71,79,83,92,100,107]. These dimensions are particularly important, as user acceptance has been identified as a key factor influencing the successful adoption and sustained use of wearable technologies in real-world settings [74,77,86,88,95].

Regarding evaluation approaches, the literature reveals a predominance of experimental and laboratory-based studies, often relying on controlled conditions and short-term assessments [1,83,102,118,121]. While these approaches enable precise measurement and validation of system performance, they may not fully capture the complexity of real working environments. Field-based studies, although less frequent, provide more realistic insights into usability, durability, and long-term effectiveness, highlighting the importance of ecological validity in the evaluation process [59,83,95,96].

Overall, the findings suggest that the assessment of wearable-based interventions is inherently multidimensional, requiring the integration of technical, physiological, and human-centered metrics [4,96,104,106,107]. However, most evaluation approaches focus primarily on system performance and short-term outcomes, with limited empirical evidence directly linking these metrics to long-term safety improvements or reductions in accident rates [88,95,109]. Additionally, the lack of standardized evaluation frameworks and the limited number of longitudinal field studies constrain the comparability of results and the ability to draw consistent conclusions regarding the real-world effectiveness of these interventions. This highlights the need for more comprehensive, standardized, and context-aware evaluation approaches in future research [74,83,105,114].

5.5. RQ5—What Are the Main Barriers, Limitations, and Challenges Affecting the Real-World Implementation of Wearable Technologies in OSH Contexts?

The analysis of the included studies indicates that the real-world implementation of wearable technologies in OSH is constrained by a combination of technical, human, organizational, and contextual challenges. These barriers highlight a gap between technological capability and practical adoption, limiting the translation of promising experimental results into sustained and measurable safety improvements [74,78,88].

From a technical perspective, several limitations affect system reliability and performance in operational environments. Sensor accuracy can be compromised by motion artifacts, environmental interference, and device misalignment, particularly in physically demanding tasks [78,88,92,109]. In addition, constraints related to battery life, data transmission, and network connectivity reduce the feasibility of continuous monitoring, especially in remote or infrastructure-limited settings. Interoperability between devices and the integration of multiple data sources also remain challenging, often leading to inconsistencies, false alarms, or reduced system robustness [74,78,84,110,111].

Human factors represent another critical dimension influencing implementation success. User acceptance is strongly affected by comfort, usability, and perceived intrusiveness. Wearable devices may introduce physical discomfort, restrict movement, or increase perceived workload, particularly during prolonged use [83,88,90]. Furthermore, concerns related to privacy, surveillance, and data misuse contribute to resistance among workers, potentially undermining trust and compliance. Social and cultural factors, including stigma associated with assistive devices, may also influence adoption in certain occupational contexts [57,58,90,100,122].

At the organizational level, economic and managerial barriers further constrain large-scale deployment. High initial investment costs, combined with maintenance requirements and infrastructure needs, pose significant challenges, particularly for small and medium-sized enterprises [74,84]. In addition, the integration of wearable systems into existing safety management processes is often complex, requiring changes in workflows, training, and data governance practices. Regulatory and ethical considerations, particularly those related to data protection and worker rights, add further complexity to implementation [57,58,78,110].

A key limitation identified across the literature is the discrepancy between laboratory-based findings and real-world performance. Many studies are conducted under controlled conditions and over short durations, which do not fully capture the variability, unpredictability, and cumulative effects present in actual work environments. As a result, the long-term usability, effectiveness, and acceptance of wearable technologies remain insufficiently validated [83,88,90,105,115].

Finally, the literature highlights that wearable technologies may, in some cases, introduce unintended risks. These include reduced situational awareness due to excessive alerts, over-reliance on automated systems, and physical constraints associated with certain devices, such as exoskeletons, which may alter natural movement patterns or affect balance [77,90,115].

Overall, the findings suggest that the successful implementation of wearable technologies in OSH depends not only on technological performance, but also on human-centered design, organizational readiness, and ethical data governance. Addressing these multi-dimensional challenges is essential to ensure that wearable systems can move beyond experimental applications and achieve sustained and measurable improvements in occupational safety outcomes under real-world conditions [57,60,74,78,105].

5.6. Relationship Between RQs

The integrated analysis of the five RQs allows us to understand the domain of wearable technologies in OSH as an interconnected system, in which each dimension contributes to a more complete view of its potential and limitations in a real-world context [74,78,88].

First, RQ1 establishes the technological basis, identifying the main types of devices and their functions associated with different categories of occupational risk. This characterization highlights that wearable technologies do not constitute a homogeneous solution, but rather a diverse set of tools with specific applications at the ergonomic, physiological, environmental, and critical event safety levels [106,109,112,120,123].

Based on this foundation, RQ2 delves deeper into the functional dimension, demonstrating how these technologies are effectively used in work contexts. The results reveal a model structured in three levels, monitoring, evaluation, and prevention, reflecting the evolution from reactive approaches to proactive and data-driven systems. Thus, RQ2 establishes the link between the technological capabilities identified in RQ1 and their practical application in risk management [100,102,104,105,108].

RQ3 introduces the effectiveness dimension, assessing the extent to which these applications produce improvements in safety outcomes. The results show that, although there is consistent evidence regarding the accuracy in risk detection and the improvement of physiological and ergonomic indicators, the demonstration of direct and sustained impacts on accident reduction remains limited. This finding highlights a mismatch between technological potential and the results observed in real-world contexts [95,102,104,105].

In this sense, RQ4 contributes to partially explaining this limitation by analyzing the metrics and approaches used in the evaluation of interventions. There is a predominance of technical and short-term indicators, often obtained in controlled environments, which makes it difficult to compare studies and evaluate organizational and long-term impacts. Thus, RQ4 shows that the limitations in evaluation condition the robustness of the conclusions regarding effectiveness identified in RQ3 [83,85,95].

Finally, RQ5 provides an integrative interpretation of implementation difficulties, identifying technical, human, and organizational barriers that affect the adoption and performance of wearable technologies in real-world contexts. These barriers help to understand why the high technical performance observed in experimental studies does not always translate into effective improvements in safety outcomes, reinforcing the importance of considering factors such as user acceptance, organizational integration, and data governance [57,58,60,78,90].

Globally, the relationship between the RQs shows a logical progression from technological characterization (RQ1), through functional application (RQ2), effectiveness evaluation (RQ3) and measurement methodologies (RQ4), to understanding implementation limitations (RQ5). This articulation demonstrates that the impact of wearable technologies on OSH depends not only on their technical capabilities, but also on the interaction between technology, user, and organizational context [74,106,121].

Thus, the results suggest that future development in this field should prioritize integrated approaches that align technological innovation with real-world validation, user acceptance, and sustainable implementation models, to realize the potential of these technologies in effectively improving workplace safety [9,89,96,105].

6. Proposed Model for the Adoption of Wearable Technologies

This section presents a conceptual proposal for the responsible adoption and implementation of wearable technologies in industrial contexts, emphasizing worker acceptance, long-term use, and the potential contribution to occupational health and safety. The proposal is based on the main findings of this SLR and aims to provide a structured basis for

organizations to plan, implement, and evaluate the introduction of these technologies in a responsible manner. Throughout this section, the factors influencing the acceptance of wearable technologies are examined, followed by the presentation of an integrative model that combines technical, human, and organizational dimensions. The section also includes considerations related to change management and the limitations associated with the proposed framework. It should be noted that the model is conceptual in nature and is intended as a guiding structure rather than a validated solution. In addition to the systematic review findings, selected complementary literature was considered to support specific theoretical dimensions, including technology acceptance, psychosocial factors, situational awareness, and data governance.

6.1. Factors Influencing the Acceptance of Wearable Technologies

The analysis of the literature indicates that the acceptance of wearable technologies in occupational health and safety contexts results from a set of interrelated factors that can be broadly organized into two main dimensions: individual factors, associated with psychological and cognitive aspects, and organizational and contextual factors, associated with the work environment. This distinction is consistent with existing theoretical approaches to technology adoption and reflects the increasing integration of technological, human, and organizational elements in contemporary monitoring systems.

At the individual level, performance expectations emerge as one of the most influential determinants of adoption. The perception that wearable technologies may contribute to improving safety conditions, reducing risks, and supporting work performance tends to increase acceptance. This finding is consistent with established acceptance models such as Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology Acceptance Model (TAM), where perceived usefulness and performance expectancy are central predictors of behavioural intention [124–126]. Empirical studies in occupational contexts further confirm that perceived usefulness and social influence significantly affect workers' willingness to adopt wearable devices [126,127].

Trust also plays a central role, particularly in situations where wearable systems involve the continuous collection of physiological, behavioral, and environmental data. Transparency in how data are collected, processed, and used is therefore essential for fostering acceptance. Research shows that concerns about data security and privacy risks can significantly reduce the intention to adopt wearable technologies, especially when sensitive biometric or location data are involved [57,58]. Prior experience with similar technologies may also reduce uncertainty and facilitate integration into daily work routines [128].

From a cognitive and behavioral perspective, perceived intrusiveness, concerns related to privacy, and the perception of control influence user attitudes. The continuous nature of monitoring may affect workers' perception of autonomy, particularly when data are associated with performance evaluation. In this context, the framing of wearable technologies as tools for protection rather than control appears to be relevant in shaping acceptance. Privacy-related concerns are widely documented in the literature, including risks associated with data misuse, unauthorized access, and surveillance, which may undermine trust if not adequately addressed [58,122].

Beyond individual perceptions, psychosocial mechanisms also influence safety-related behaviours. Recent research demonstrates that team dynamics, emotional exhaustion, and safety self-efficacy play a mediating role in shaping safety behaviour in high-risk environments [60]. This suggests that the effectiveness of wearable technologies may not be fully understood without considering the broader psychological and social context in which they are implemented.

At the organizational level, the safety climate represents an important factor. Work environments in which safety is visibly prioritized tend to facilitate the acceptance of monitoring technologies [128]. Acceptance is also influenced by the definition of use cases, with higher acceptance generally associated with applications clearly oriented toward worker protection, such as hazard detection or fatigue monitoring. In contrast, applications perceived as focused on productivity or surveillance may generate resistance.

Additional factors include job characteristics, such as job stability and the nature of tasks, as well as facilitating conditions related to usability, ergonomics, and integration into existing workflows. Social influences, including management support and communication strategies, also contribute to shaping acceptance. Approaches that involve workers in decision-making processes, such as device selection and implementation planning, may reduce resistance and support adoption [128].

Technological characteristics, including accuracy, reliability, comfort, and interoperability, also influence acceptance. The increasing integration of different data sources may enhance the perceived usefulness of these systems, although this may also introduce additional concerns related to data management and complexity. For example, wearable sensor systems have demonstrated strong capabilities for fatigue detection and physiological monitoring, potentially supporting proactive safety interventions [102].

Overall, the acceptance of wearable technologies appears to result from the interaction between individual perceptions, organizational conditions, and technological characteristics. Trust, perceived usefulness, psychosocial conditions, and alignment with safety objectives are particularly relevant within organizational environments that promote transparency and participation.

6.2. Integrative Model for the Implementation of Wearable Technologies

Based on the synthesis of the SLR, a conceptual integrative model for the implementation of wearable technologies in industrial contexts is proposed. The structure of the model reflects the main themes identified across the reviewed studies, particularly those related to technology application, worker acceptance, organizational readiness, and data-driven risk management. The model aims to organize these elements into a structured framework that combines technical, human, and organizational dimensions within a progressive and iterative process.

The model is structured into four interconnected phases, whose schematic representation is presented in Figure 5. Although these phases are described sequentially, the model should be interpreted as dynamic, allowing for feedback between stages and continuous adaptation throughout the implementation process.

The first phase involves defining the focus and identifying appropriate use cases. It is essential to clearly establish the purpose of implementation, with particular attention to safety-related objectives. The literature suggests that use cases oriented toward risk prevention and worker protection tend to be more acceptable than those focused primarily on performance monitoring [128]. Limiting data collection to the work context may reduce perceived intrusiveness and contribute to building trust. Voluntary adoption, supported by non-coercive incentives, may also facilitate acceptance.

The second phase focuses on preparing the organizational environment and fostering trust. The development of a strong safety climate is an important element, as it supports the perception that wearable technologies are introduced as part of a broader strategy for worker protection. Transparent communication regarding data collection, processing, and use is essential, particularly when dealing with sensitive information. Privacy and security concerns are consistently identified as major barriers to adoption, as wearable systems may expose workers to risks related to data breaches, unauthorized access, or misuse of

personal information [57,58]. Furthermore, inconsistencies in data governance practices and lack of transparency in privacy policies may further undermine trust [57].

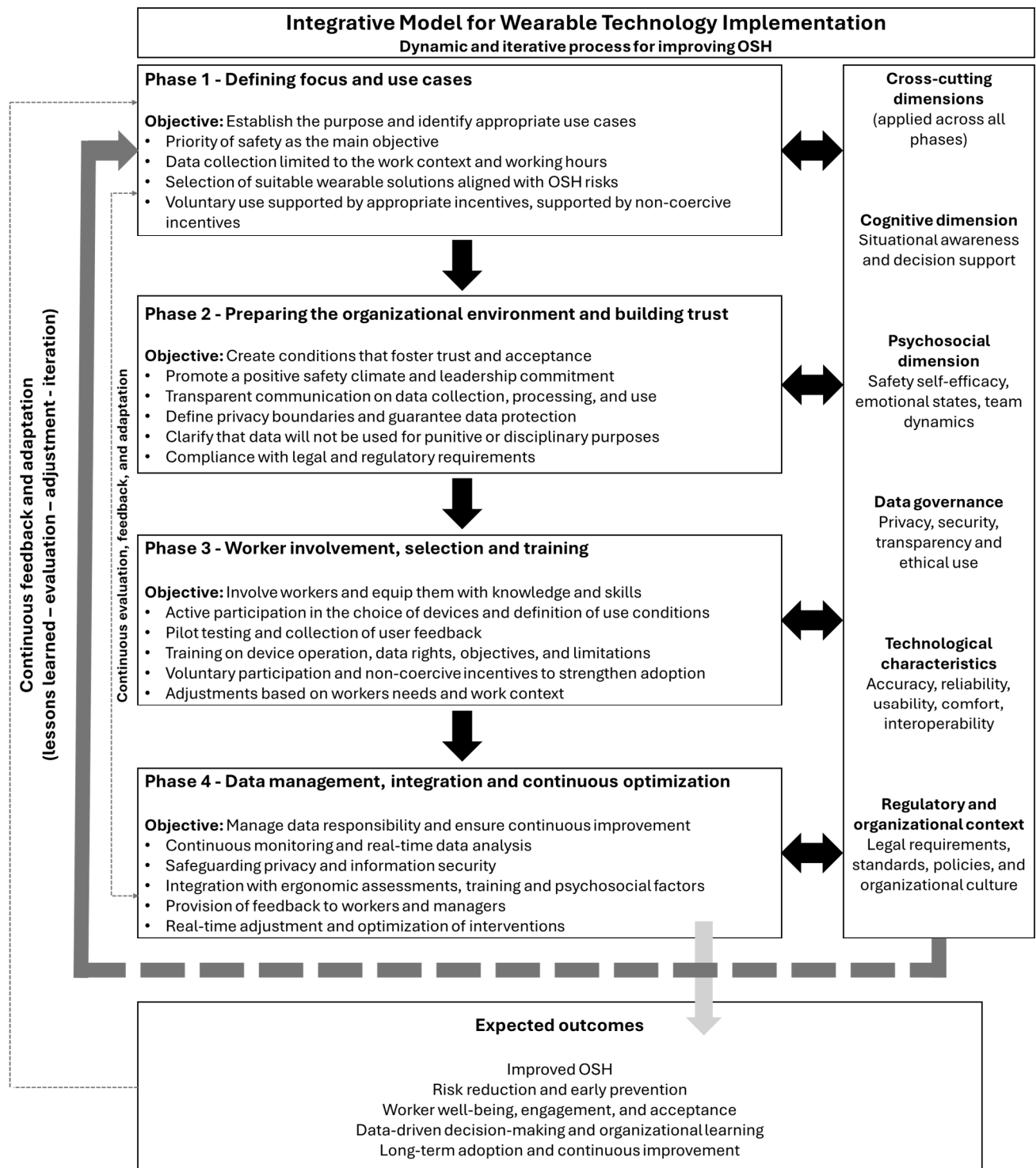


Figure 5. Conceptual integrative model for the implementation of wearable technologies in OSH.

The third phase emphasizes worker involvement in the implementation process. The literature indicates that active participation in device selection and the definition of usage conditions may contribute to improved acceptance [128]. Voluntary participation, combined with structured training, supports informed use and reduces uncertainty regarding the implications of wearable technologies. Participatory approaches, such as pilot testing

and user feedback, allow technologies to be adjusted to the specific needs of workers and work environments.

The fourth phase focuses on data management, system integration, and continuous improvement. Wearable technologies typically operate within broader digital infrastructures that enable continuous data collection and analysis. These systems may support the identification of risk patterns and contribute to preventive actions, although their effectiveness depends on data quality, interpretation, and context. Importantly, the translation of data into safe behaviour is not automatic and involves cognitive processes. Situation awareness plays a central role in this transition, as it integrates perception, comprehension, and projection of environmental information, enabling workers to anticipate hazards and respond effectively [56].

The model also highlights the importance of integrating technical data with human and organizational factors. In addition to physical indicators, psychosocial aspects, including perceived exertion, emotional states, and cognitive workload, may also influence safety outcomes. This perspective reflects a broader understanding of occupational health, in which technological systems interact with psychological and organizational conditions [60].

To enhance the practical applicability of the model, the conceptual structure can be operationalized through concrete actions, indicators, and responsibilities, as presented in Table 1.

Table 1. Operationalization of the proposed integrative model for wearable technology implementation.

Phase	Practical Actions	Possible Indicators	Responsible Actors
Phase 1—Defining focus and use cases	Define safety-oriented use cases; limit data collection to work-related purposes; identify suitable wearable solutions	Use-case clarity; perceived usefulness; alignment with OSH risks	Management; OSH team; supervisors
Phase 2—Preparing the organizational environment and building trust	Communicate data purposes; define privacy boundaries; clarify non-punitive use of data	Trust level; privacy acceptance; worker perception of fairness	Management; Human Resources; legal/data protection officer; OSH team
Phase 3—Worker involvement, selection, and training	Involve workers in device selection; conduct pilot testing; provide training on use, rights, and limitations	Participation rate; training completion; usability feedback; acceptance intention	Workers; supervisors; OSH team; technology providers
Phase 4—Data management, integration, and continuous optimization	Establish data governance; monitor indicators; provide feedback; adjust interventions	Data access rules; feedback frequency; intervention records; worker-reported workload	OSH team; Information Technology/data team; management; worker representatives

6.3. Positioning of the Proposed Model in Relation to Existing Frameworks

The proposed model should be interpreted as a conceptual framework complementary to existing theoretical approaches to technology adoption and socio-technical systems. Established models such as TAM and UTAUT explain individual acceptance through constructs such as perceived usefulness, effort expectancy, social influence, and trust [124,125].

Previous research has applied these approaches to wearable technologies, highlighting the importance of perceived usefulness, privacy risk, and social influence as key determinants of adoption [126,127]. However, these models tend to focus primarily on intention to use rather than on the broader implementation process. The proposed model extends this perspective by organizing implementation as a multi-phase process that includes organizational preparation, worker involvement, and data management considerations. It also

integrates cognitive and psychosocial dimensions, such as situation awareness and emotional factors, which are not explicitly addressed in traditional acceptance models [56,60].

From a socio-technical perspective, the model emphasizes the interaction between technological capabilities, human factors, and organizational conditions, considering wearable technologies as part of a broader system rather than isolated tools. Its contribution lies in integrating these dimensions into a structured framework that supports implementation planning, while explicitly acknowledging that it is conceptual in nature and intended as a structured synthesis of existing evidence rather than a validated implementation framework.

6.4. Recommendations for Change Management

The implementation of wearable technologies involves organizational change processes that require planning, communication, and monitoring. Transparent communication regarding the purpose of data collection is essential to reduce resistance and build trust. Clarifying that data are not intended for punitive use may help mitigate concerns related to surveillance.

Training plays a relevant role in supporting implementation, particularly when it addresses both technical operation and broader objectives, including data rights and privacy considerations. Involving workers in decision-making processes may contribute to reducing perceptions of imposed monitoring.

Privacy, surveillance, and data governance require particular attention. Wearable technologies generate large volumes of sensitive data, which may be subject to misuse or unauthorized access. Research shows that current wearable ecosystems often present inconsistencies in data governance and transparency, highlighting the need for stronger regulatory and organizational frameworks [57]. Additionally, risks related to data breaches and unauthorized access remain a significant concern in wearable IoT systems [58].

The integration of wearable technologies into digital infrastructures may support monitoring and decision-making processes. However, these systems should be implemented with appropriate safeguards, ensuring ethical data use and maintaining worker trust.

6.5. Limitations of the Proposed Model

The proposed model presents several limitations that should be considered when interpreting its scope and applicability.

Firstly, the model is conceptual and has not been empirically validated. Its application in real-world contexts requires further investigation to assess its effectiveness and adaptability.

Secondly, the model is based on a heterogeneous body of literature, including studies with different methodologies and levels of empirical support. This may limit the comparability of findings and the generalizability of the framework.

Additionally, the evidence is concentrated in specific sectors, and the applicability of the model to other contexts may require adaptation. Organizational, cultural, and regulatory differences may also influence implementation.

The model also assumes a certain level of organizational maturity and technological infrastructure, which may not be present in all settings. Implementation may therefore present challenges in contexts with limited resources.

Finally, the rapid evolution of wearable technologies introduces challenges related to interoperability, scalability, and data governance. These factors highlight the need for adaptive implementation approaches and further research focused on empirical validation.

7. Conclusions

This section summarizes the main results obtained, highlighting the study's contributions to understanding the application of wearable technologies in OSH, as well as the practical implications and limitations identified.

7.1. General Conclusions

The increasing digitalization of work environments has accelerated the development of wearable technologies as tools to support OSH. This SLR synthesized evidence from 60 selected studies to examine the types of wearable technologies applied, their functions in risk monitoring and prevention, their effectiveness, evaluation approaches, and the main barriers to real-world implementation.

The results indicate that wearable technologies are primarily used for continuous monitoring of physiological, biomechanical, and environmental risk factors, enabling more detailed and real-time data collection than traditional assessment methods. This capability supports a transition from reactive safety management toward more data-driven and potentially proactive approaches. However, the current evidence base is predominantly focused on detection and monitoring capabilities rather than on demonstrated long-term safety outcomes.

The review shows that wearable technologies are increasingly integrated with AI and predictive analytics, allowing the identification of complex patterns and the anticipation of risk conditions. These approaches highlight the potential of data-driven safety systems, although their effectiveness depends not only on algorithmic performance but also on how information is interpreted and translated into action within real work contexts. In this regard, cognitive mechanisms such as situational awareness play a relevant role in linking data acquisition to safe behaviour.

Despite these advances, the findings reveal that empirical evidence regarding the direct impact of wearable technologies on accident reduction remains limited and heterogeneous. Most studies are conducted in controlled or short-term settings, which constrains the generalizability of results to dynamic and complex workplace environments. Therefore, the current literature supports the potential of wearables for improving risk detection and supporting decision-making, but does not yet provide consistent evidence of sustained improvements in safety outcomes.

The review also highlights that the implementation of wearable technologies is influenced by multiple interacting factors, including technical performance, user acceptance, organizational readiness, and data governance. Human and organizational dimensions, such as trust, perceived intrusiveness, safety climate, and psychosocial conditions, are particularly critical for successful adoption. Concerns related to privacy, surveillance, and ethical data use remain significant barriers, reinforcing the need for transparent and responsible implementation strategies.

In response to the identified gaps, this study proposes a conceptual integrative model structured into four phases: (i) definition of use cases, (ii) preparation of the organizational environment, (iii) worker involvement and training, and (iv) data management and continuous improvement. The model aims to provide a structured synthesis of the literature by integrating technical, human, and organizational dimensions within a process-oriented framework. However, it should be emphasized that this model is conceptual in nature and intended as a guiding structure rather than a validated implementation tool.

Overall, the findings suggest that wearable technologies should not be understood as standalone solutions, but as components of broader socio-technical systems. Their effectiveness depends on the alignment between technological capabilities, human factors, and

organizational conditions. Consequently, the successful adoption of wearable technologies in OSH requires integrated, human-centered, and context-sensitive approaches.

7.2. Limitations of the Study and Proposed Model

Several limitations should be considered when interpreting the findings of this review. First, although a systematic methodology based on the PRISMA framework was adopted, the search strategy may not have captured all relevant studies due to database selection, indexing variability, and differences in terminology across disciplines. Despite the use of an expanded set of keywords, the multidisciplinary nature of wearable technologies in OSH may result in the omission of some relevant contributions.

Second, the review included only English-language publications, which may have excluded studies published in other languages and limited the representation of certain geographical or cultural contexts. In addition, the exclusion of grey literature, such as technical reports and industry documents, may have reduced the integration of practical and applied perspectives.

Third, the included studies present substantial methodological and contextual heterogeneity, encompassing experimental studies, field studies, prototype developments, and conceptual approaches. This diversity limits direct comparability between studies and prevented the use of quantitative meta-analysis. As a result, the findings should be interpreted as indicative trends rather than definitive conclusions.

Another limitation relates to the nature of the available evidence. Much of the literature is based on controlled experiments, small samples, or short-term evaluations, which restricts the ability to assess long-term effectiveness and real-world applicability. Furthermore, many studies focus on technical performance rather than on organizational or behavioral outcomes, contributing to an incomplete understanding of the overall impact of wearable technologies.

The proposed integrative model is also subject to important limitations. It is a conceptual framework derived from the synthesis of heterogeneous literature and has not been empirically validated. Its applicability in real-world contexts remains uncertain and may require adaptation to different sectors, organizational structures, and regulatory environments.

Finally, the model assumes a certain level of technological and organizational maturity, which may not be present in all contexts, particularly in small and medium-sized enterprises or resource-constrained environments. These factors may affect both the feasibility and the effectiveness of implementation.

7.3. Proposals for Future Work

The findings of this review highlight several directions for future research. A primary priority is the empirical validation of wearable technologies and the proposed implementation model in real-world contexts. Longitudinal field studies are needed to assess sustained use, long-term safety outcomes, and the interaction between technological systems and organizational practices.

Future research should also focus on improving methodological consistency, including the development of standardized evaluation frameworks that integrate technical, physiological, behavioral, and organizational indicators. This would enhance comparability between studies and strengthen the evidence base regarding effectiveness.

Another important direction concerns the integration of human and psychosocial factors. Further studies should explore how variables such as trust, safety self-efficacy, emotional states, and team dynamics influence the adoption and effectiveness of wearable

technologies. This would contribute to a more comprehensive understanding of safety as a socio-technical phenomenon.

The ethical dimension represents a critical area for future work. Research should address issues related to data privacy, informed consent, transparency, and governance, as well as the balance between monitoring and worker autonomy. The development of clear regulatory and organizational frameworks is essential to ensure responsible implementation.

Technological validation is also required, particularly regarding the reliability, robustness, and interoperability of wearable systems in dynamic environments. Independent testing and real-world validation are necessary to bridge the gap between laboratory performance and operational use.

Finally, future research should explore the integration of wearable technologies with emerging digital systems, including IoT, AI, and immersive technologies such as virtual and augmented reality. These developments may enhance training, situational awareness, and decision support, contributing to more adaptive and resilient safety systems.

In summary, advancing the field requires multidisciplinary and context-sensitive research that combines technological innovation with human-centered design, organizational integration, and ethical responsibility.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
IoT	Internet of Things
JB	Joanna Briggs Institute
OSH	Occupational Safety and Health
PPE	Personal Protective Equipment
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses

RQs	Research Questions
SLR	Systematic Literature Review
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
WoS	Web of Science

Appendix A

Appendix A.1

Table A1 summarizes the assessment of the methodological quality of the included studies, based on criteria such as objectives, context, methods, data collection and analysis.

Table A1. Assessment of the methodological quality of the included studies based on the JBI quality criterion.

Reference	Type of Study	Clear Objective	Defined Context	Appropriate Method	Rigorous Data Collection	Coherent Analysis	Relevant Results	Limitations Discussed	Overall Score	Ranking
[88]	Field experimental study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[83]	Experimental	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[96]	Experimental/field study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[77]	Delphi study/mixed-method	Yes	Yes	Yes	Partial	Yes	Yes	Yes	6.5	High
[107]	Experimental study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[121]	Case study/experimental	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[106]	Experimental/data-driven study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[114]	Experimental/AI-based study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[104]	Experimental study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[105]	Experimental/ML study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[95]	Pilot/usability study	Yes	Yes	Yes	Partial	Yes	Yes	Yes	6.5	High
[115]	Experimental/biomechanics study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[109]	Prototype/conceptual and experimental	Yes	Yes	Partial	Partial	Yes	Yes	No	5.0	Low
[129]	Experimental/engineering system	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[78]	System design/applied research	Yes	Yes	Yes	Partial	Partial	Yes	Yes	6.0	Moderate
[117]	Experimental study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[130]	Experimental validation study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High

Table A1. Cont.

Reference	Type of Study	Clear Objective	Defined Context	Appropriate Method	Rigorous Data Collection	Coherent Analysis	Relevant Results	Limitations Discussed	Overall Score	Ranking
[119]	Experimental/deep learning study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[131]	Experimental/sensor platform development	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[118]	Field feasibility study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[102]	Experimental/machine learning study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[90]	Preliminary field experimentation	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[103]	Prototype/IoT validation study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[132]	Prototype/IoT system study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[59]	Experimental/wearable bioelectronics study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[133]	Prototype/IoT fall detection study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[108]	Device development/laboratory and field validation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[84]	Prototype/IoT-enabled PPE study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[94]	Proof-of-concept/prototype study	Yes	Yes	Partial	Partial	Yes	Yes	Yes	6.0	Moderate
[89]	System development/experimental validation	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[71]	Experimental/AI-based wearable system	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[76]	Experimental/smart PPE HAR study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[72]	Proof-of-concept/system validation	Yes	Yes	Yes	Partial	Yes	Yes	Yes	6.5	High
[82]	Experimental/machine learning ergonomics study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[73]	System design/experimental AI-IoT evaluation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High

Table A1. Cont.

Reference	Type of Study	Clear Objective	Defined Context	Appropriate Method	Rigorous Data Collection	Coherent Analysis	Relevant Results	Limitations Discussed	Overall Score	Ranking
[101]	Experimental/EMG anomaly detection study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[75]	Prototype/wearable monitoring solution	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[79]	Prototype/IoT smart insole study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[81]	Preliminary experimental study	Yes	Yes	Yes	No	Yes	Yes	Yes	6.0	Moderate
[91]	Feasibility/wearable biosensor ML study	Yes	Yes	Partial	Partial	Yes	Yes	Yes	6.0	Moderate
[85]	Feasibility/wearable sensor study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[100]	Design and experimental validation study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[7]	Machine learning/stress prediction study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[99]	Design and experimental evaluation study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[93]	System framework/applied validation	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[112]	Experimental/ML-based biomechanical risk study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[80]	Experimental/wearable heat-stress monitoring study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[116]	Prototype/sensor compliance study	Yes	Yes	Yes	Partial	Partial	Yes	Yes	6.0	Moderate
[113]	Field study/workload risk modelling	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[29]	Experimental/IMU-based WMSD risk assessment study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[110]	Cloud-based IoT monitoring study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[87]	Machine learning/near-fall detection study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[123]	Design and pilot validation study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High

Table A1. *Cont.*

Reference	Type of Study	Clear Objective	Defined Context	Appropriate Method	Rigorous Data Collection	Coherent Analysis	Relevant Results	Limitations Discussed	Overall Score	Ranking
[98]	Prototype/IoT and ML study	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[111]	Poster/conceptual prototype system	Yes	Yes	Partial	Partial	Partial	Yes	Partial	5.0	Low
[92]	Experimental ergonomics study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[134]	Multimodal clustering/field monitoring study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7.0	High
[86]	Lab-based simulation/smart textile study	Yes	Yes	Yes	Yes	Yes	Yes	Partial	6.5	High
[97]	Prototype/IoT wearable system	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate
[74]	System proposal/wearable monitoring framework	Yes	Yes	Yes	Partial	Yes	Yes	Partial	6.0	Moderate

Appendix A.2

Table A2 presents the inter-rater agreement matrix used to assess the consistency between the two authors of this study in the classification of the methodological quality of the included studies. The matrix summarizes the distribution of classifications independently assigned by each author across the three quality levels (High, Moderate, and Low).

Table A2. Confusion matrix of the methodological quality ratings assigned by the two reviewers.

Reviewer 1 \ Reviewer 2	High	Moderate	Low	Total
High	34	5	0	39
Moderate	0	19	0	19
Low	0	0	2	2
Total	34	24	2	60

Appendix A.3

Table A3 summarizes the 60 articles included in this study. For each study, the research objective and main contributions were analyzed.

Table A3. Summary of the 60 studies included in the SLR.

Reference	Research Objective	Main Contributions
[88]	To evaluate manufacturing workers' perceptions of discomfort, distraction, and burden associated with wearing inertial sensors during multiple work shifts.	The study demonstrates that wearable inertial sensors are generally well accepted by workers, with low levels of discomfort, distraction, and perceived burden. Factors such as non-neutral postures and higher body mass index slightly increased negative perceptions, though effects were minimal. The findings support the feasibility of long-term wearable sensor use in occupational settings for exposure assessment.
[83]	To investigate whether back-support exoskeletons improve work posture among masons using AI-based pose estimation techniques.	The study shows that back-support exoskeletons provide minimal improvements in posture despite reducing muscle activity. The findings challenge their effectiveness as a solution for postural correction in construction tasks, highlighting the need for critical evaluation before widespread adoption.
[96]	To develop and validate a wearable system for continuous physiological monitoring of work-related stress over 24 h periods.	The study demonstrates that wearable devices can reliably monitor physiological stress indicators such as heart rate variability and pulse transit time in real-world conditions. Results show clear differences between work and non-work stress levels, supporting the use of wearable technologies for continuous occupational health monitoring.
[77]	To identify and assess safety risks and mitigation strategies associated with exoskeleton use in construction tasks.	The study identifies 10 critical safety risks and 12 mitigation strategies related to exoskeleton use. It highlights the importance of addressing human–robot interaction risks and provides practical guidance for improving safety and adoption in construction environments.
[107]	To develop a multimodal method for assessing physical fatigue using wearable sensors combining physiological and kinematic data.	The study proposes an integrated fatigue assessment approach combining heart rate, skin temperature, and kinematic data (jerk), validated against perceived exertion. The method enables real-time fatigue monitoring and offers a more comprehensive and practical solution for workplace safety.
[121]	To evaluate the effort, comfort, and acceptance of passive back-support exoskeletons in both laboratory and field conditions.	The study reveals significant discrepancies between laboratory and field performance of exoskeletons, showing reduced effectiveness and acceptance in real-world conditions. It emphasizes the importance of field validation and highlights comfort and usability as key factors for adoption.
[106]	To develop a wearable sensor-based approach for continuous assessment of occupational heat stress in construction workers.	The study proposes a data-driven framework using physiological signals and machine learning to assess heat strain, achieving over 92% prediction accuracy. It highlights the importance of individualized monitoring and demonstrates the effectiveness of wearable biosensors for real-time occupational safety management.
[114]	To develop and evaluate a training platform for human–robot collaboration in construction using wearable physiological sensing and immersive technologies.	The study introduces an innovative training system that uses physiological data to assess cognitive load during human–robot collaboration. Results show the platform can effectively evaluate training performance and improve safety outcomes by linking cognitive load to safety behavior.

Table A3. Cont.

Reference	Research Objective	Main Contributions
[104]	To investigate the impact of physical fatigue on construction workers' situational awareness using wearable sensor data.	The study demonstrates that physical fatigue significantly reduces hazard recognition and safety risk assessment performance. Wearable sensors effectively capture fatigue through heart rate and heart rate variability, confirming their value for real-time safety monitoring and decision-making.
[105]	To develop an early detection system for physical fatigue in industrial environments using wearable sensors and contextual data.	The study shows that combining biometric and contextual data significantly improves fatigue detection accuracy. The approach reduces false negatives and enhances real-time safety interventions, supporting Industry 5.0 human-centered safety systems.
[95]	To evaluate the feasibility and usability of wearable sensors for monitoring construction workers' physiological status during on-duty and off-duty activities.	The study confirms the usability of wearable sensors for monitoring worker health and behavior. It highlights variability in physiological responses and identifies practical challenges in applying wearable technologies within total worker health frameworks.
[115]	To evaluate the impact of passive back-support exoskeletons on fall risk indicators during slip and trip events.	The study shows that exoskeleton use alters biomechanical responses and may negatively affect balance recovery, potentially increasing fall risk. It highlights the need for improved design and usage guidelines for safe implementation.
[109]	To develop and evaluate a sensor-integrated smart shirt for monitoring posture and movement in occupational settings.	The study presents a wearable smart textile prototype capable of monitoring upper body movement in real time. It highlights design challenges and demonstrates the potential of smart clothing for ergonomic assessment and human-machine interaction.
[129]	To develop a self-powered wearable sensing system for fall detection and vibration risk monitoring in construction workers.	The study introduces a self-powered triboelectric sensor system capable of detecting falls and monitoring vibration exposure with high accuracy (~94%). It integrates sensing, power generation, and machine learning for real-time safety monitoring.
[78]	To design and evaluate a wearable IoT-based system for monitoring worker health and safety in remote and hazardous environments.	The study presents an integrated IoT system combining wearable sensors, networking, and real-time analytics tailored for remote environments. It emphasizes contextual data integration and user-centered monitoring approaches.
[117]	To evaluate the use of wearable sensor data for improving occupational cold stress assessment.	The study shows that continuous physiological monitoring provides better insight into cold stress than traditional methods. It highlights variability between individuals and the limitations of generalized models, supporting personalized assessment approaches.
[130]	To evaluate the accuracy of a non-invasive sensor for measuring core body temperature under heat stress conditions.	The study shows that the Dräger Double Sensor produced temperature estimates close to rectal temperature measurements during heat exposure. It supports the potential use of non-invasive wearable temperature monitoring for workers exposed to heat stress or protective clothing, while emphasizing the need for further validation under varied occupational conditions.

Table A3. Cont.

Reference	Research Objective	Main Contributions
[119]	To develop and evaluate a wearable sensor-based deep learning approach for recognizing fishermen's behaviours during fishing operations.	The study demonstrates that multimodal fusion of accelerometer and gyroscope data improves behaviour recognition accuracy. The proposed model achieved high classification performance and shows strong potential for monitoring human-related risk factors and improving maritime occupational safety.
[131]	To develop a wearable SERS platform for rapid field detection of antineoplastic drug contamination in medical workplaces.	The study introduces a flexible wearable detection platform capable of identifying icotinib and gefitinib residues on work surfaces and packaging within minutes. It contributes a practical method for occupational exposure monitoring and risk reduction in healthcare environments.
[118]	To investigate the feasibility of using electrodermal activity collected from wearable sensors to assess construction workers' perceived risk during ongoing work.	The study shows that electrodermal responses differ significantly between low- and high-risk activities. It demonstrates the feasibility of using wearable physiological sensing as a continuous, objective, and non-intrusive method for assessing perceived risk in construction safety management.
[102]	To classify worker fatigue under diverse thermal conditions using wearable physiological sensors and machine learning.	The study shows that combining electromyography, heart rate, heart rate variability and thermal condition data improves real-time fatigue classification. The models achieved high predictive accuracy, supporting proactive fatigue management in construction and other physically demanding industries.
[90]	To preliminarily evaluate the use of a passive back-support exoskeleton in a real industrial warehouse context.	The study reports reduced muscle activation and improved posture during lifting tasks when using the exoskeleton. It also suggests reduced perceived fatigue and increased operator confidence, while noting the need for further research due to the preliminary nature of the study.
[103]	To develop and validate an IoT-based smart helmet for real-time mining safety monitoring.	The study presents a helmet integrating environmental, physiological, motion and helmet-removal sensors with LoRa/cloud-based alerting. The prototype achieved high detection accuracy, low latency and strong communication reliability under simulated mining conditions, supporting its potential for high-risk industrial environments.
[132]	To develop a wearable smart glove system for real-time miner health monitoring and location tracking.	The study proposes a glove-based system integrating temperature, pulse, motion and fall-detection sensors with wireless communication and a mobile dashboard. It demonstrates the potential to reduce emergency response delays by continuously monitoring miner health and movement in hazardous environments.
[59]	To develop a field-deployable wearable bioelectronic system for monitoring stress in outdoor workers under hot conditions.	The study introduces a soft wearable device integrating electrodermal activity and temperature sensing with nanofabric radiative cooling. It improves thermal management, reduces motion artifacts and supports continuous real-time stress monitoring during outdoor work activities.

Table A3. Cont.

Reference	Research Objective	Main Contributions
[133]	To develop a wearable IoT-based fall detection system for workers in confined industrial spaces.	The study proposes a waist-worn system using dual tri-axial accelerometers and a threshold-based algorithm to detect falls and prolonged inactivity. Its main contribution is a simple, low-cost and real-time alerting solution that avoids complex machine learning and supports rapid supervisor response.
[108]	To develop and validate a wearable monitor for characterizing personal exposure to particulate matter and volatile organic compounds.	The AirPen combines physical sample collection with low-cost sensors for particulate matter, volatile organic compounds, environmental variables, location and motion. The study demonstrates its usefulness for identifying exposure sources by time, location and activity, advancing occupational and environmental exposure assessment.
[84]	To design a Smart PPE vest for real-time hazard detection and worker health monitoring in worksites.	The study presents a vest integrating environmental and biometric sensors with LoRa communication, local alerts, GPS tracking and mobile app notifications. It contributes a scalable smart PPE concept for improving hazard detection and emergency response in infrastructure-limited worksites.
[94]	To design and implement a multi-modal wearable system for proactive monitoring of physiological distress in industrial workers.	The study integrates photoplethysmography, electrodermal activity, skin temperature and ambient volatile organic compound sensing into a compact wearable device. It demonstrates early detection of heat-stress indicators under controlled conditions and proposes a roadmap toward personalized machine learning and federated learning for industrial deployment.
[89]	To develop a mobile health monitoring and alert application for agricultural workers using multiple wearable sensors.	The study presents a smartphone-based system integrating pulse oximetry, skin temperature and inertial measurement unit data via Bluetooth low-energy signaling. It enables real-time monitoring, anomaly alerts and automatic reconnection, offering a scalable framework for agricultural and broader occupational safety applications.
[71]	To develop an AI-based wearable sensor system to assess the safety of workers during manual load lifting.	The study proposes a smart safety jacket integrating barometric, accelerometer and magnetometer data to detect lifting events and classify whether lifting was performed safely. The system achieved high accuracy and contributes to automated prevention of low back pain and musculoskeletal injury risks.
[76]	To design and evaluate a non-invasive smart helmet system for human activity recognition in worker safety applications.	The study develops a certification-compliant smart helmet integrating motion and environmental sensors. It evaluates several machine learning pipelines and shows that XGBoost provides the best balance between accuracy, latency and computational efficiency for on-board activity recognition.

Table A3. Cont.

Reference	Research Objective	Main Contributions
[72]	To design and validate a wireless-powered smart PPE system for monitoring correct PPE usage in industrial IoT environments.	The study presents a battery-free smart PPE prototype using ultra high frequency radio frequency identification power harvesting, radio frequency identification communication and capacitive sensing. It demonstrates feasible wireless power and communication up to 4 m, supporting real-time monitoring of PPE compliance without batteries.
[82]	To automate ergonomic risk assessment in manual material handling using sEMG wearable sensors and machine learning.	The study demonstrates that sEMG data can classify ergonomic risk levels associated with lifting tasks based on the NIOSH lifting equation. Machine learning models, especially Decision Tree, achieved very high accuracy, supporting automated ergonomic monitoring beyond visual posture assessment.
[73]	To develop and evaluate an IoT- and AI-based smart hearing protection system for high-noise industrial environments.	The study proposes intelligent hearing protection that selectively attenuates hazardous noise while preserving speech and safety notifications. It integrates voice activity detection, adaptive filtering and indoor localization, improving speech intelligibility and targeted safety communication in noisy workplaces.
[101]	To evaluate the impact of a passive shoulder-support exoskeleton on muscle strain using electromyography-based anomaly detection.	The study applies feature engineering and Isolation Forest anomaly detection to electromyography signals collected during lifting tasks with and without exoskeleton support. Results indicate fewer muscle-strain anomalies when the exoskeleton is used, supporting its potential ergonomic benefit.
[75]	To develop a wearable monitoring solution to improve safety for sewer and septic tank cleaning workers.	The study proposes a wearable kit integrating gas sensors, heart-rate monitoring, communication modules and emergency alerts. It contributes a real-time safety monitoring approach for workers exposed to toxic gases, enabling supervisor oversight and rapid emergency response.
[79]	To design and implement a smart insole system for monitoring back pain risk and lifting techniques among older workers.	The study uses plantar pressure sensors and real-time wireless processing to classify lifting techniques. The system achieved high classification accuracy and showed good user acceptance, supporting smart insoles as a less intrusive tool for ergonomic monitoring.
[81]	To examine the feasibility of estimating human core temperature from heart rate data for occupational heat-stress monitoring.	The study evaluates heart-rate-based core temperature estimation during work tasks in a climate chamber. Results suggest reasonable approximation during work phases but weaker performance during recovery, highlighting the need for further model refinement before workplace deployment.
[91]	To assess the feasibility of integrating wearable cortisol sensor data with machine learning for identifying physical fatigue in construction workers.	The study develops a sweat cortisol sensor and combines cortisol-related impedance changes with physiological metrics for fatigue classification. Support Vector Machine achieved the best classification performance, supporting cortisol as a promising biomarker for proactive fatigue monitoring.

Table A3. Cont.

Reference	Research Objective	Main Contributions
[85]	To assess the feasibility of an FBG-based wearable system for monitoring back dorsal flexion-extension in video terminal workers.	The study shows that a smart textile with Fiber Bragg Grating sensors can detect dorsal flexion–extension movements over time. It supports the potential of lightweight, non-invasive optical fiber wearables for monitoring poor postural habits and preventing back musculoskeletal disorders.
[100]	To design and validate FleXo, a flexible passive back-support exoskeleton for reducing lower back strain during manual handling tasks.	The study introduces a lightweight and flexible passive exoskeleton optimized to reduce perceived effort during lifting while preserving freedom of movement. User feedback indicates improved comfort, satisfaction and potential benefits for reducing low back strain in occupational manual handling.
[7]	To develop and validate a real-time worker stress prediction framework for smart factory assembly lines using wearable physiological data and machine learning.	The study uses physiological indicators such as heart rate, respiration rate and skin conductance to predict worker stress. XGBoost achieved the strongest performance, suggesting that IoT-enabled wearable monitoring can support proactive stress management and improve worker wellbeing and productivity.
[99]	To design and evaluate a passive shoulder exoskeleton based on a variable stiffness torque generator for industrial applications.	The study presents a compact, lightweight passive shoulder exoskeleton with adjustable torque assistance. Experimental results show reduced muscle effort during overhead reaching and load lifting, supporting its use for repetitive industrial tasks and WMSD prevention.
[93]	To propose a wearable occupational health and safety assurance system for power operation workers in complex environments.	The study presents a wearable framework integrating vital-sign monitoring, wireless communication and SVM-based life-status assessment. It supports real-time evaluation of operator health and early warning of risks caused by abnormal physical conditions during power operations.
[112]	To develop an automatic method using inertial wearable sensors and machine learning to classify biomechanical risk during load lifting.	The study uses IMUs placed on the sternum and lumbar region to discriminate biomechanical risk classes based on the Revised NIOSH Lifting Equation. Results show high classification performance, with the sternum emerging as the most informative sensor location.
[80]	To analyze occupational heat stress using a sensor-based wearable safety helmet from an environmental ergonomics perspective.	The study demonstrates that a sensor-based helmet can monitor environmental variables, heat stress indices and physiological indicators under different work conditions. It supports individualized heat-stress awareness and site-specific occupational safety interventions.
[116]	To design and test a Hall-effect sensor system for monitoring safety goggle compliance.	The study demonstrates that Hall-effect sensing can detect safety eyewear position and movement related to compliance. Although static detection had limited success, movement-based matched filtering distinguished compliance-related transitions, supporting smart PPE compliance monitoring.
[113]	To develop a practical method for estimating individual construction workers' workload risk based on physical activity, work conditions and age.	The study combines wearable heart-rate and activity data with WBGT and worker age to estimate workload risk. The proposed model achieved strong accuracy and provides a practical approach for health-risk judgement on construction sites.

Table A3. Cont.

Reference	Research Objective	Main Contributions
[29]	To develop and evaluate an IMU-based wearable system for objective work-related musculoskeletal disorder risk assessment.	The study presents a wearable IMU system with orientation estimation, joint-angle measurement and ergonomic risk evaluation. It aligns with established methods such as RULA, REBA, Strain Index and Rodgers analysis, while enabling more detailed and targeted ergonomic intervention.
[110]	To develop and evaluate a cloud-based infrastructure for real-time health monitoring in emergency response scenarios.	The study presents a scalable cloud architecture for monitoring vital signs of paramedics and emergency workers using wearable devices. Its main contribution is demonstrating large-scale deployment, real-time alarm management and improved operational safety in emergency response contexts.
[87]	To improve slip, trip and fall prevention by detecting real-world near-fall events using wearable IMU data and machine learning.	The study uses real occupational near-fall data from 110 workers and evaluates multiple neural network architectures. It shows that CNN and InceptionTime models can effectively classify near-fall events, supporting more ecologically valid fall-prevention systems.
[123]	To design and validate a modular smart chair system for improving workplace ergonomics and reducing risks associated with prolonged sitting.	The study introduces a smart chair integrating pressure sensing, vibration, LED feedback and BLE communication. Pilot testing showed high posture-detection accuracy and rapid user response to alerts, supporting its use for sedentary workplace health monitoring.
[98]	To develop smart gloves for preventing hand injuries in manufacturing plants using IoT sensors and One-Class SVM.	The study proposes gloves that monitor grip strength, finger angle and environmental risks, using One-Class SVM to detect abnormal or hazardous patterns. It contributes a proactive wearable approach for identifying hand-injury risks and improving manufacturing safety.
[111]	To present Smart_Safe, an AI-driven modular safety system for indoor industrial environments using wearable sensors and Auto-ID technologies.	The poster outlines a platform for real-time worker tracking, fall detection, zone violation detection and collision prevention between workers and mobile robots or forklifts. Its main contribution is the integration concept combining wearables, Auto-ID, edge computing and digital twins, although empirical validation appears limited.
[92]	To evaluate the effects of a liquid-cooled garment worn under protective equipment on subjective thermal strain, physiological responses and ergonomics during intermittent exercise.	The study shows that liquid cooling under PPE reduces perceived heat strain, body temperature increase and heart rate without negatively affecting ergonomic features. It supports wearable cooling garments as a strategy to reduce heat burden in protective ensembles.
[134]	To develop and validate an adaptive multimodal clustering framework for occupational health risk monitoring using wearable sensor data.	The study integrates physiological, activity and location data from highway-maintenance workers. It identifies interpretable behavioral–physiological states and provides spatiotemporal risk mapping, supporting context-aware occupational health surveillance.
[86]	To assess the feasibility and accuracy of smart textile systems for classifying occupational manual material handling tasks.	The study demonstrates that smart socks and a smart shirt can classify simulated MMH tasks with very high accuracy. It supports smart textiles as promising tools for ergonomic exposure assessment and occupational injury prevention.

Table A3. Cont.

Reference	Research Objective	Main Contributions
[97]	To develop an affordable smart wearable vest for monitoring construction worker health in harsh environments.	The Vital Vest integrates WBAN and IoT technologies with sensors for heart rate, SpO ₂ , temperature and activity/fall detection. It contributes a low-cost, energy-efficient monitoring solution for real-time alerts and worker safety in construction environments.
[74]	To propose a wearable-based monitoring system for power utility linemen to mitigate workplace health and safety risks.	The study applies the smart connected worker concept by integrating physiological, physical and environmental sensing into PPE, connected to a mobile app and cloud analytics platform. It contributes a framework for real-time and offline supervision, supporting accident prevention and improved safety procedures in power utilities.

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